

Multi-Model Ensemble Wake Vortex Prediction

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Knowledge for Tomorrow

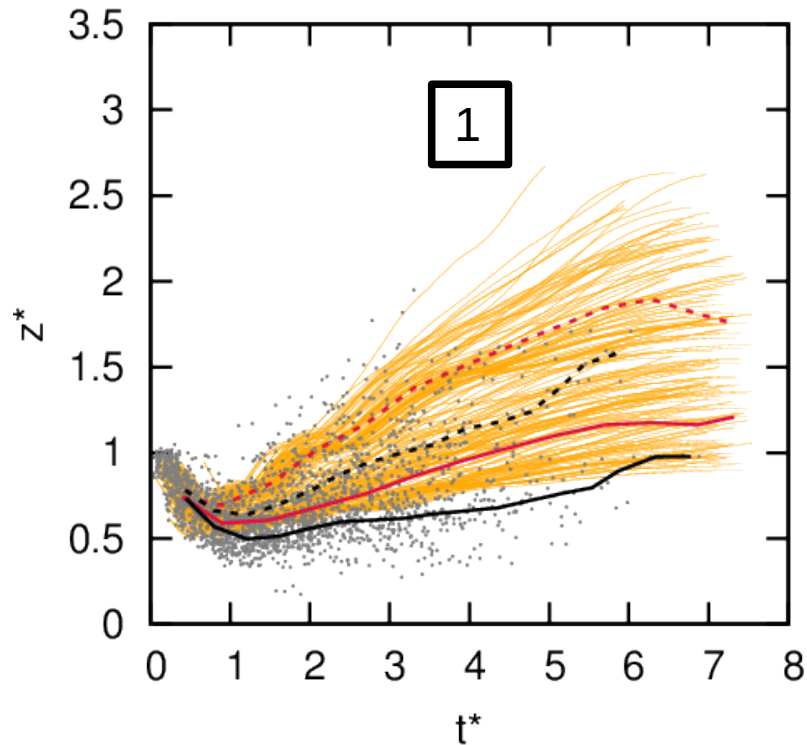




Revision of P2P - Motivation

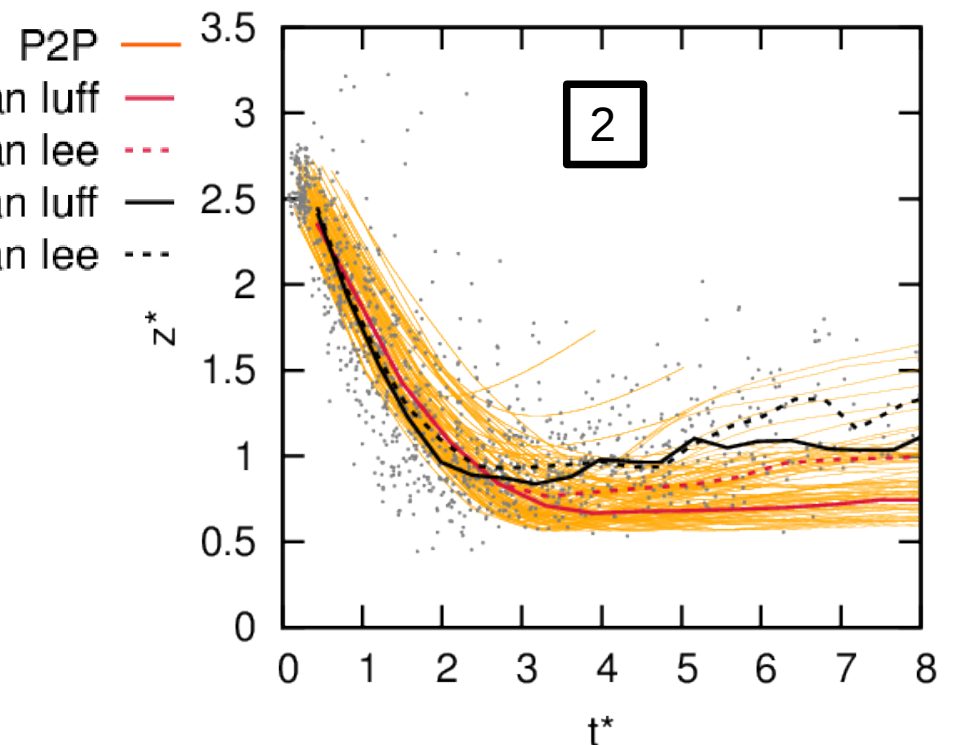
wake vortex descent

WakeFRA



88 landings

WakeMUC



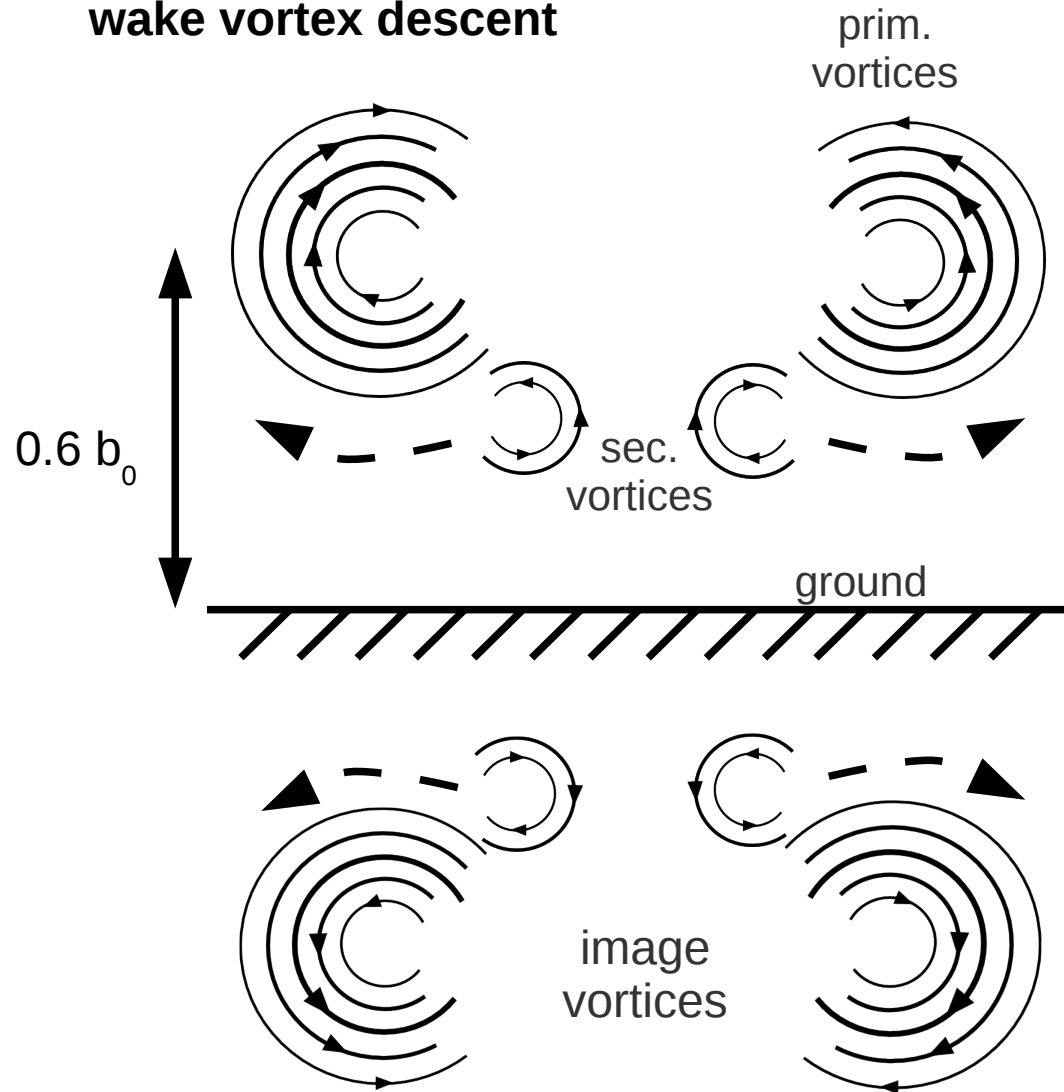
70 landings

$\Gamma^* = \Gamma / \Gamma_0$, $z^* = z / b_0$, $y^* = y / b_0$, $t^* = t / t_0$
 b_0 = initial vortex spacing
 w_0 = initial vortex descent speed



Revision of P2P

wake vortex descent



1

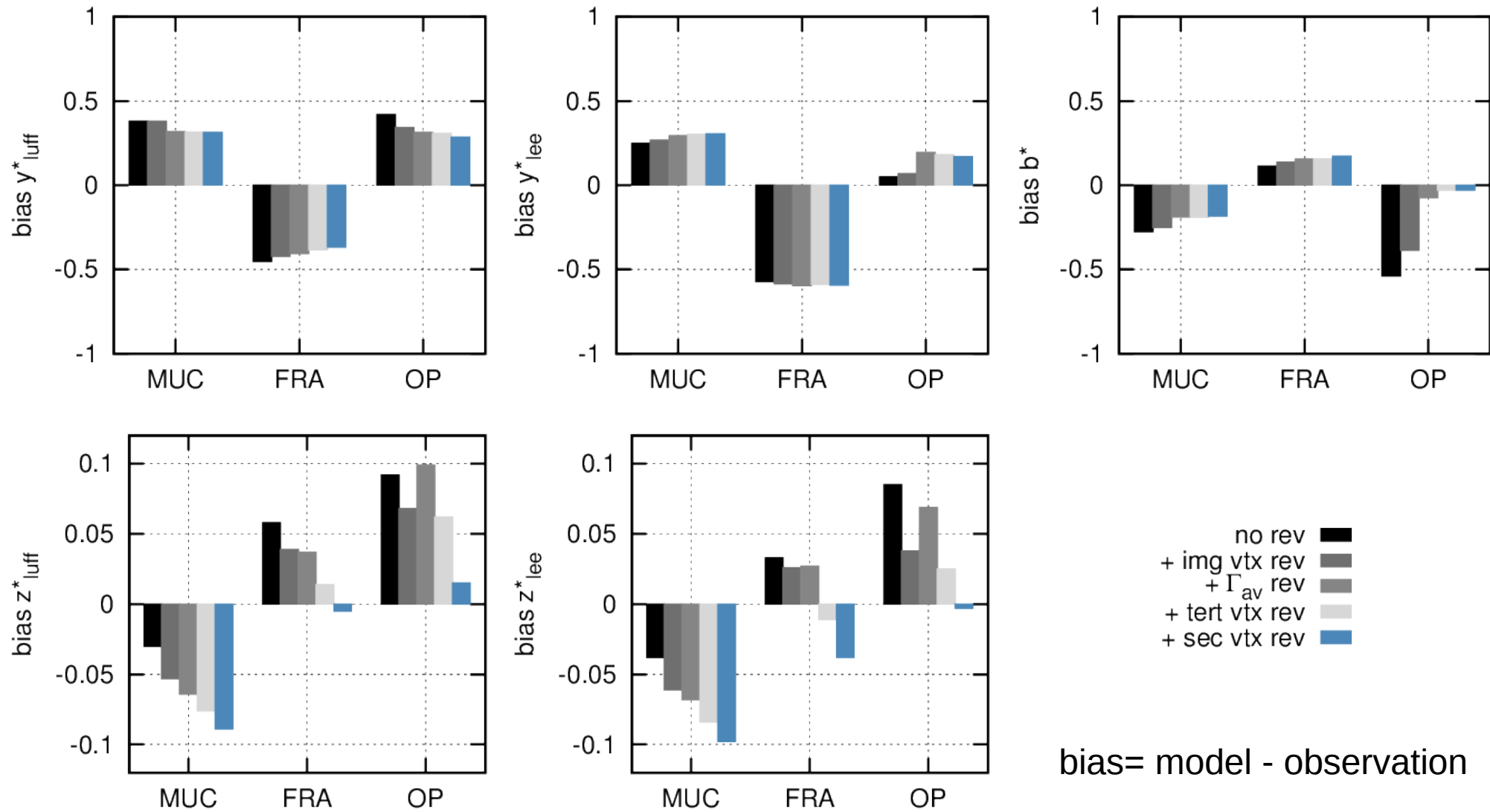
- secondary vortices weakened by 30 % after first round
- tertiary vortices weakened by 30 % from the beginning ($0.7 * \Gamma_{\text{sec}}$)

2

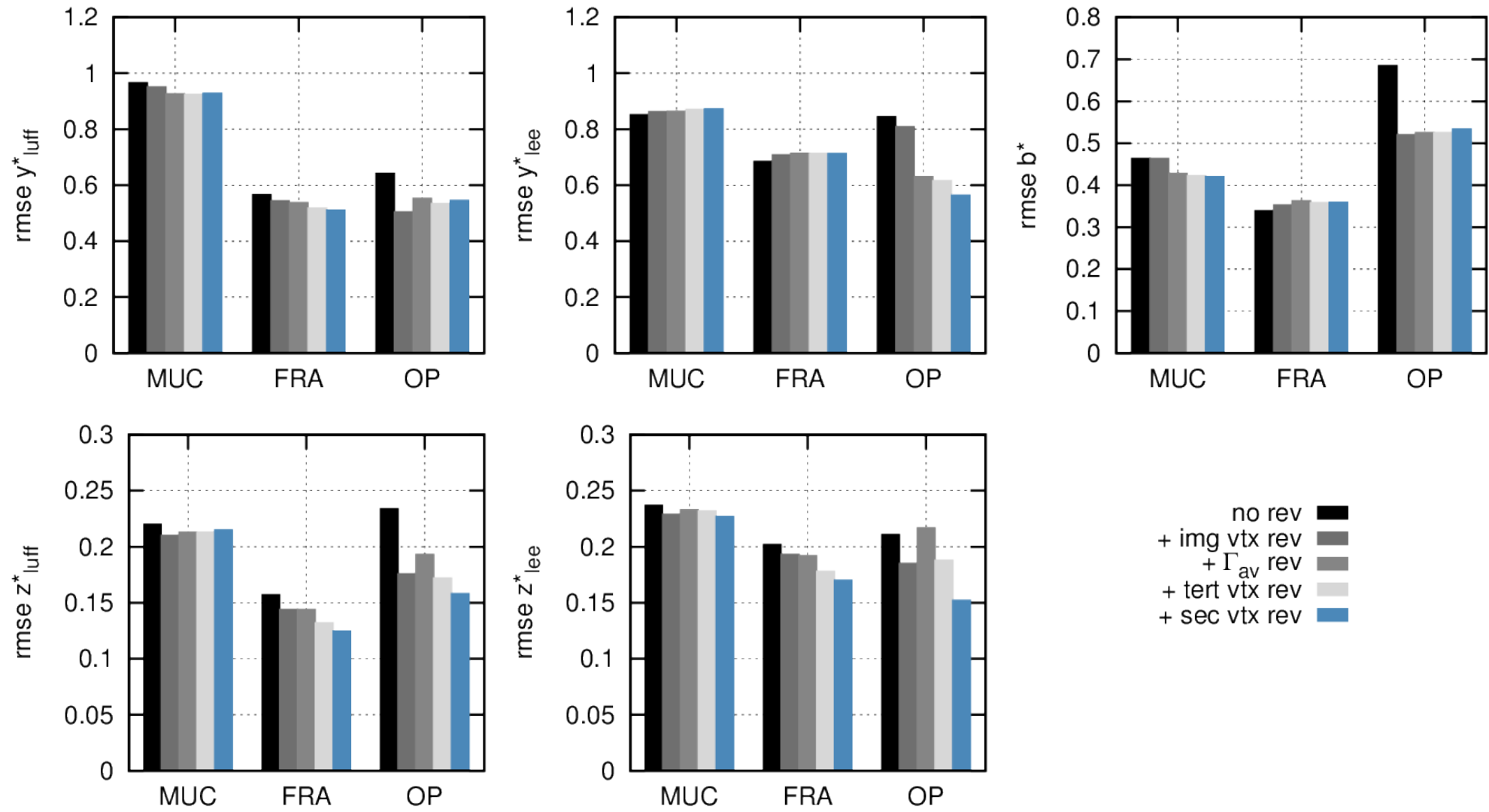
- vortex-ground interaction above $0.6 b_0$: not yet further investigated
- vortex ground interaction not only distance but also time dependent ?



Revision of P2P



Revision of P2P



Multi Model Ensemble

Sugar

How to mix several good ingredients?

Water

Lemon Juice

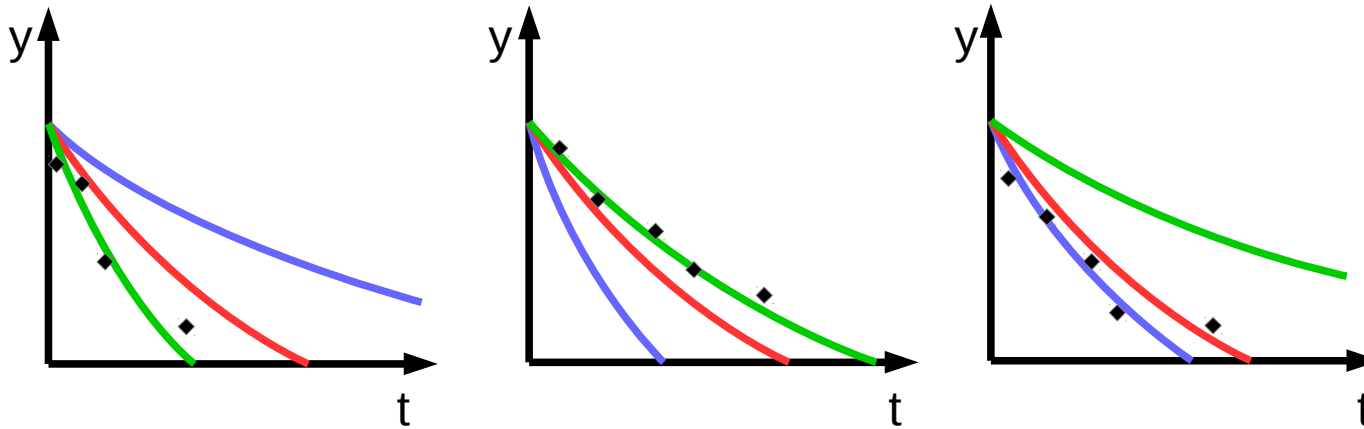
Lemonade



Why not use the best ensemble member exclusively?

Why not use the best ensemble member exclusively?

- which is the best member?
- in average best performing member can sometimes be the worst one



Can an ensemble outperform its best member?

- success of ensemble appr.: any model can be the best sometimes
- consistently low performing models → no increase of skill

Yes!

Hagedorn et al., 2005



Ensemble Members

NASA-DLR cooperation

D2P

- deterministic output of P2P
- based on decaying potential vortex, adapted to LES results (DLR)

TDP 2.1

- considers effect of crosswind shear on vortex descent (NASA)

APA 3.2

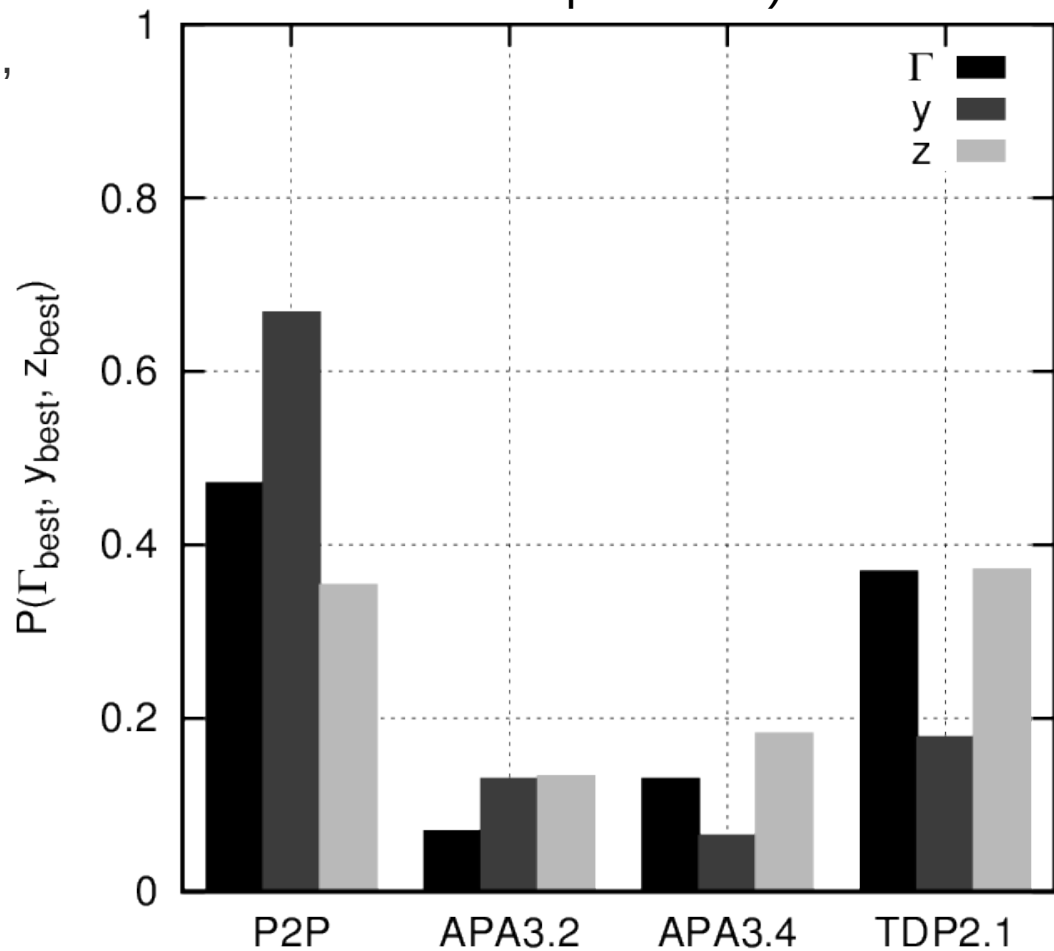
- decay and transport model according to Sarpkaya (NASA)

APA 3.4

- reduced effect of stratification (NASA)

Probability that one of the models delivers the best forecast

(in ground-effect, on the basis of rmse for 99 example cases)



Multi-Model Ensemble

Reliability Ensemble Averaging (REA)

$$\tilde{f} = \tilde{A}(f) = \frac{\sum_i R_i f_i}{\sum_i R_i}$$

model
performance
(a-priori)

model
convergence



iteration
loop



Giorgi and Mearns, 2002

$$R_i = [(R_{B,i})^m \cdot (R_{D,i})^n]^{[1/(m \cdot n)]} = \left\{ \left[\frac{nv}{abs(B_i)} \right]^m \left[\frac{nv}{abs(D_i)} \right]^n \right\}^{[1/(m \cdot n)]}$$

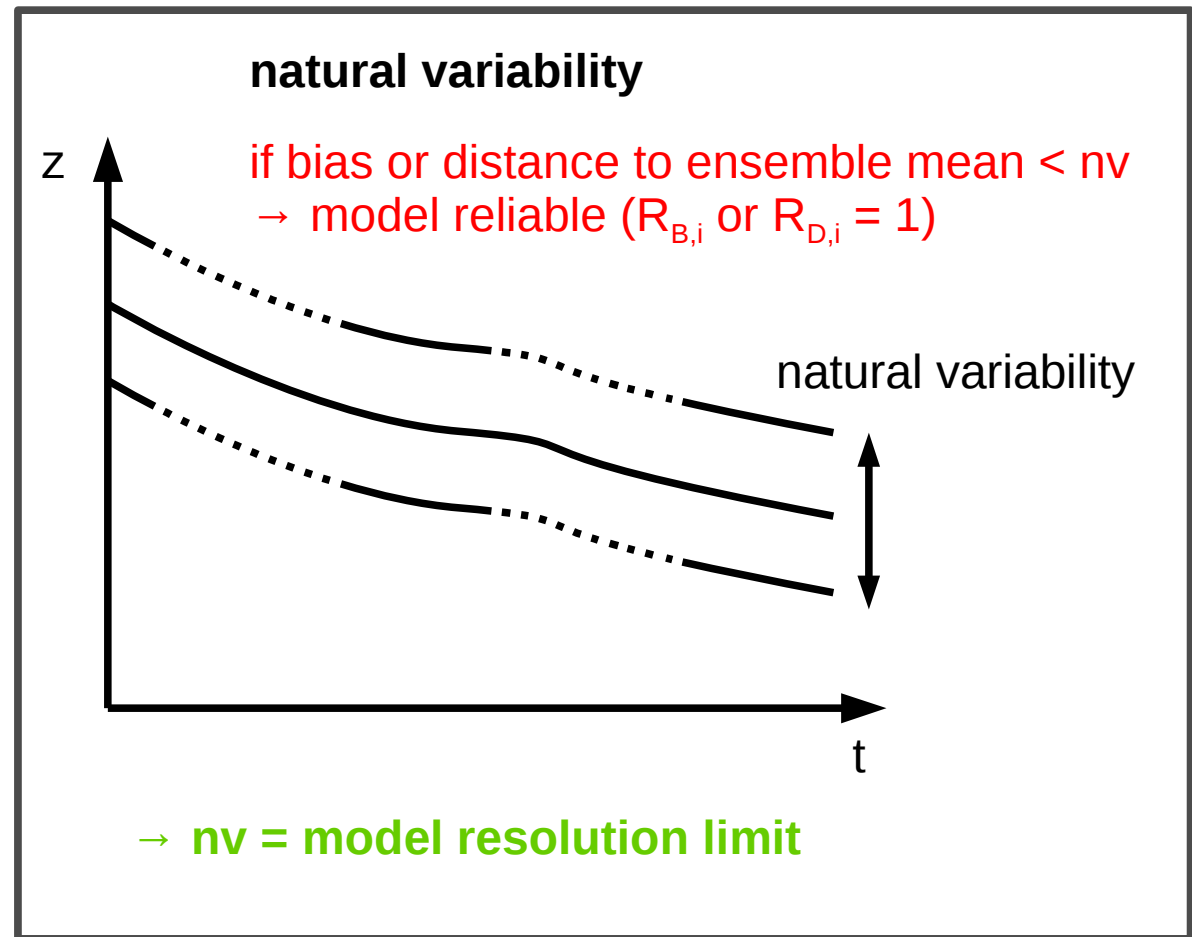
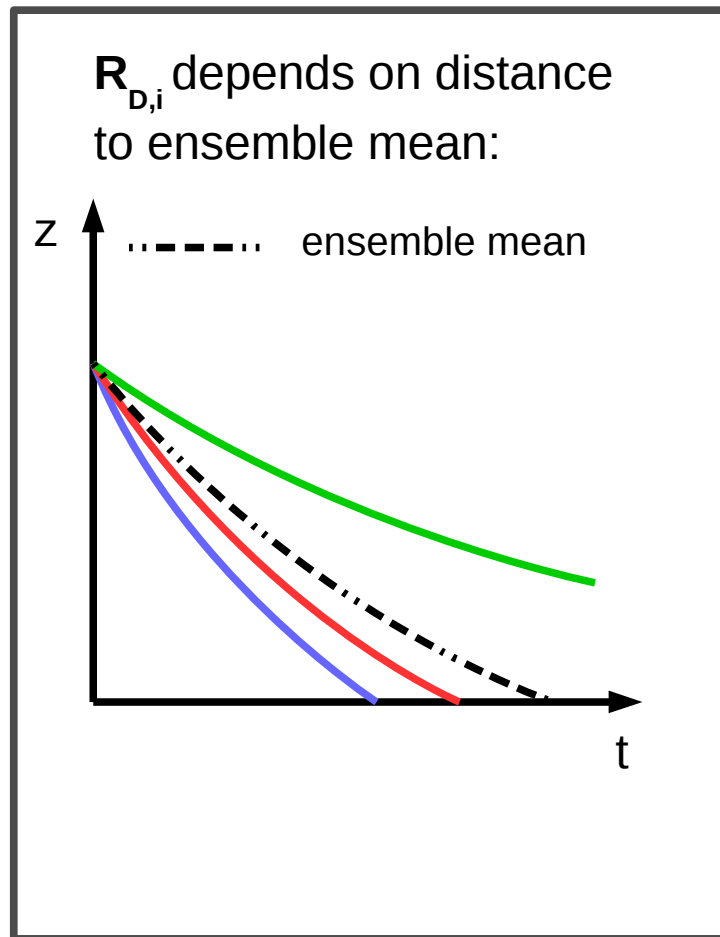
f_i = forecast of model i
 $\tilde{A}(f)$ = REA-forecast
 R_i = reliability factor of model i

nv = natural variability
 B_i = absolute bias of model i
 D_i = absolute difference between forecast of model i and ensemble mean



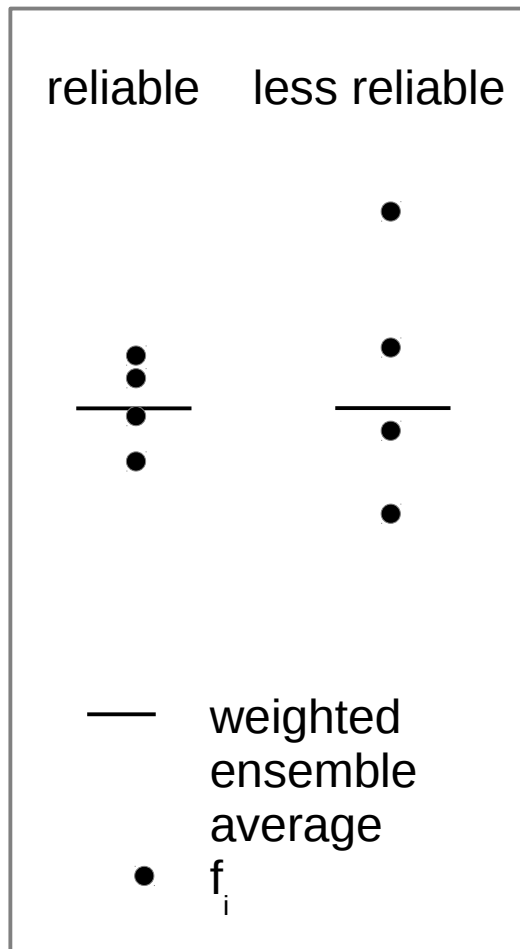
Multi-Model Ensemble

Reliability Ensemble Averaging



Multi-Model Ensemble

Reliability Ensemble Averaging uncertainty bounds:

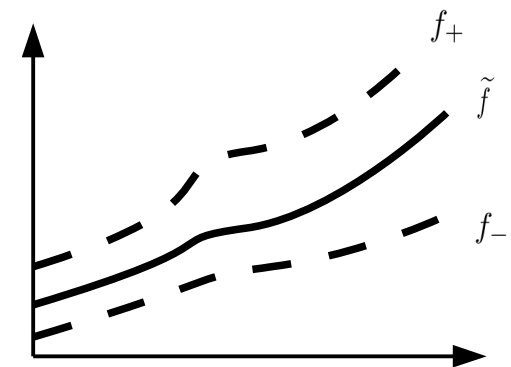


$$\tilde{\delta}_f = [\tilde{A}(f_i - \tilde{f})^2]^{1/2} = \left[\frac{\sum_i R_i (f_i - \tilde{f})^2}{\sum_i R_i} \right]^{1/2}$$

uncertainty bounds depend on ensemble spread

$$f_+ = \tilde{f} + \tilde{\delta}_f$$

$$f_- = \tilde{f} - \tilde{\delta}_f$$



according to Giorgi and Mearns, 2002



Application to Wake Vortex Models

Reliability Ensemble Averaging

Training

- mixture of landings from WakeFRA, WakeMUC and WakeOP
- 95 selected cases

$R_{B,i}$ and $R_{D,i}$

- $R_{B,z,i}(t), R_{B,y,i}(t), R_{B,\Gamma,i}(t), R_{D,z,i}(t), R_{D,y,i}(t), R_{D,\Gamma,i}(t)$
- $\Delta t^* = 2 t_0$
- separately for luff and lee vortices
- weights for reliability factors: $R_{B,z,i} : m=1.0, R_{D,z,i} : n=0.3$

Uncertainty envelope

- initial condition uncertainty added (not considered in original approach):

variable	unit	σ (standard deviation)
true airspeed	[m/s]	4
air density	[kg/m ³]	0.0048
weight	[kg]	1300
z0	[m]	7
y0	[m]	25

variable	unit	σ (standard deviation)
if initial conditions derived from lidar:		
z0	[m]	9
y0	[m]	13
Γ_0	[m ² /s]	13



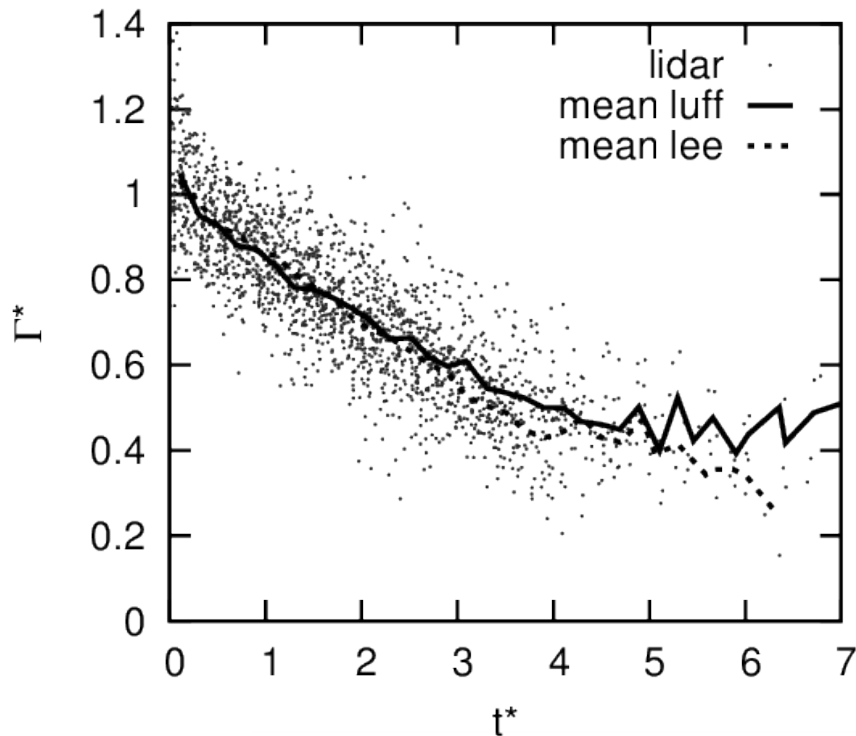
Application to Wake Vortex Models

REA natural variability, Γ^*

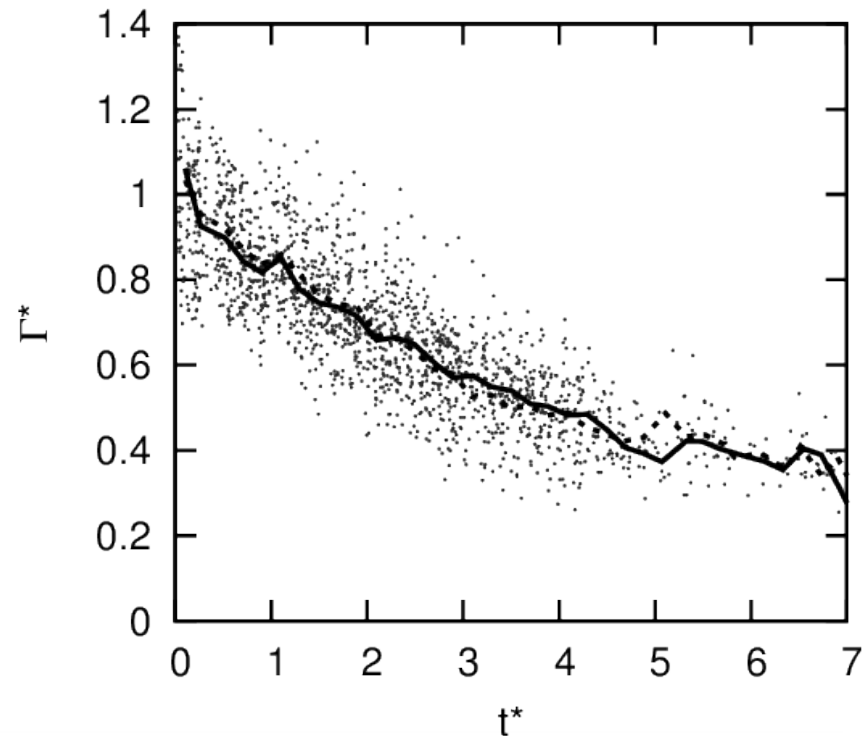
$$\begin{aligned} N^* &= N^* t_0 \\ \varepsilon^* &= (\varepsilon^* b_0)^{1/3} / w_0 \\ v^* &= v / w_0 \end{aligned}$$

	$N^* < 0.3, \varepsilon^* > 0.25$	$N^* < 0.3, \varepsilon^* < 0.25$
$\sigma_{obs, \Gamma_{luff}^*}$	0.097 (1073)	0.094 (956)
$\sigma_{obs, \Gamma_{lee}^*}$	0.081	0.096

$\varepsilon^* > 0.2, N^* < 0.3$



$\varepsilon^* < 0.2, N^* < 0.3$



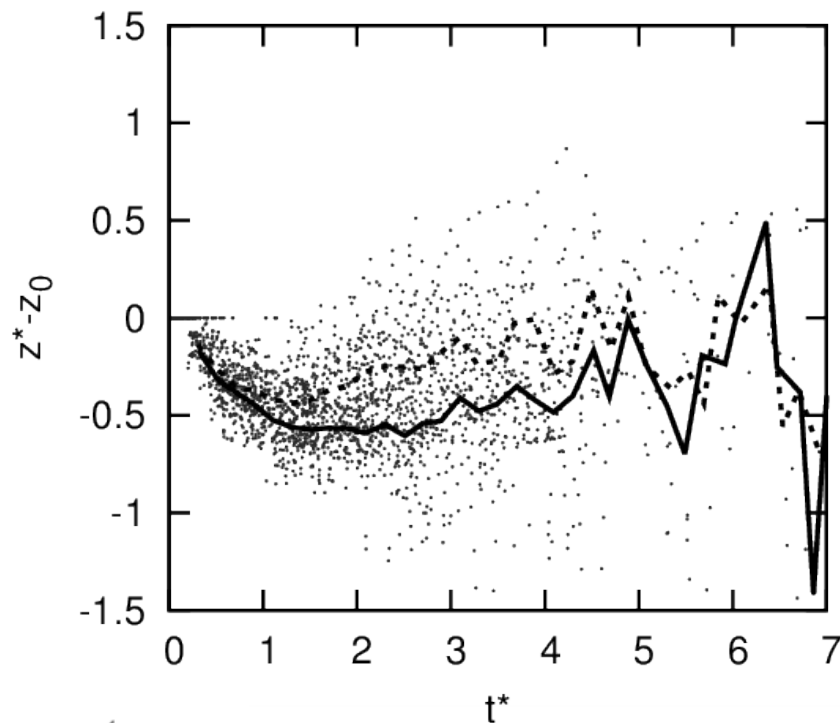
Application to Wake Vortex Models

REA natural variability, z^*

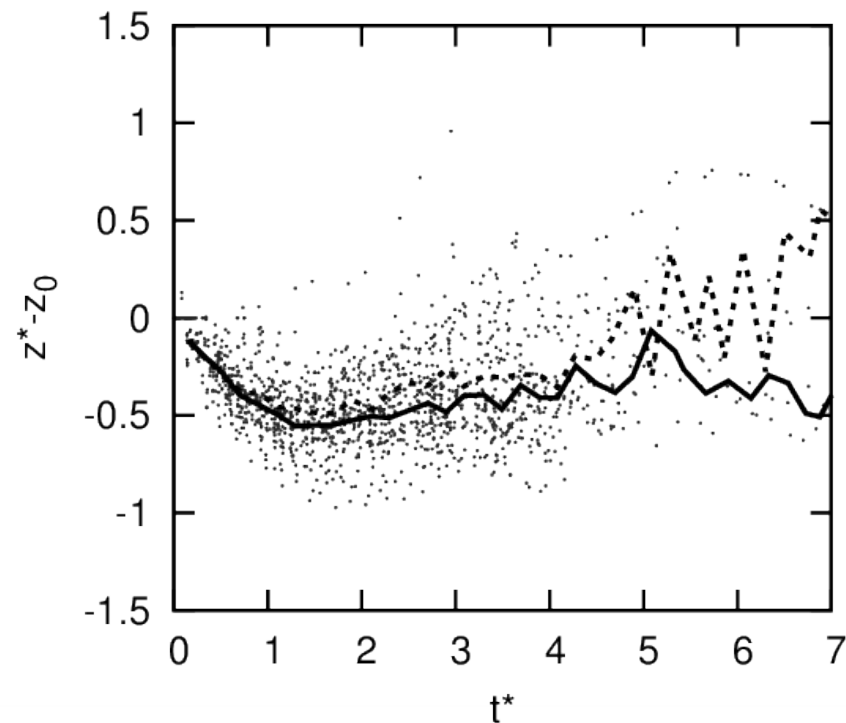
$$\sigma_{obs} = \sqrt{\sigma_{err}^2 + \sigma_{nv}^2}$$

	$N^* < 0.3, v^* > 0.5$	$N^* < 0.3, v^* < 0.5$
σ_{obs, z_{luff}^*}	0.35 (1224)	0.200 (805)
σ_{obs, z_{lee}^*}	0.35	0.262

$|v^*| > 1.0, N^* < 0.3$



$|v^*| < 1.0, N^* < 0.3$



Results

REA forecast

(one single landing)

enhancement:

$$\text{rmse}_{z^*, \text{TDP}} = 0.158$$

$$\text{rmse}_{z^*, \text{REA}} = 0.148$$

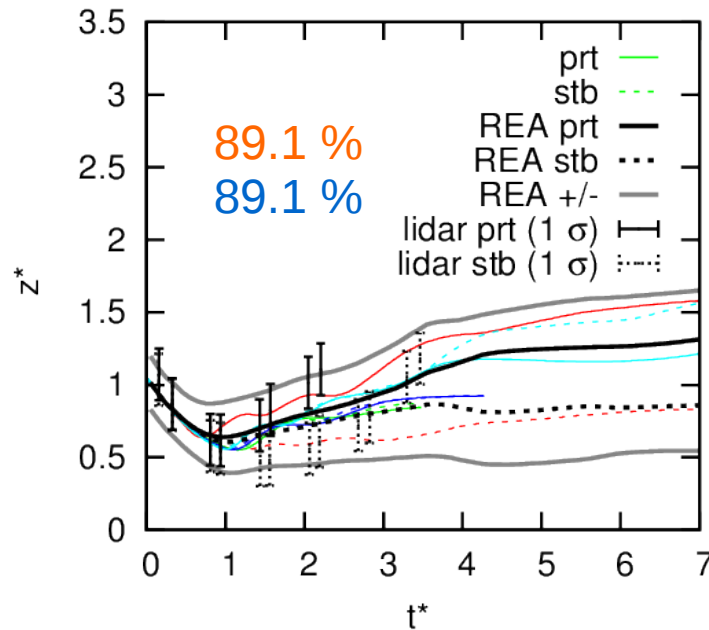
$$\text{rmse}_{\Gamma^*, \text{D2P}} = 0.085$$

$$\text{rmse}_{\Gamma^*, \text{REA}} = 0.072$$

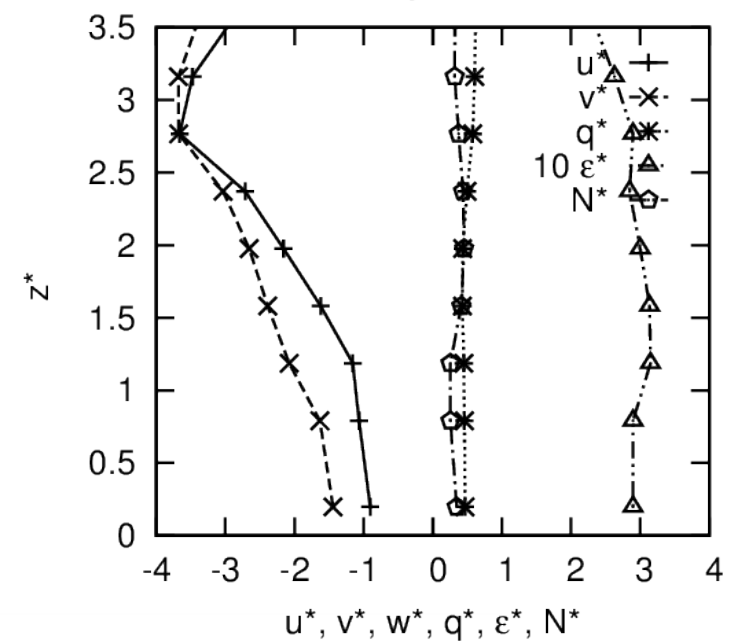
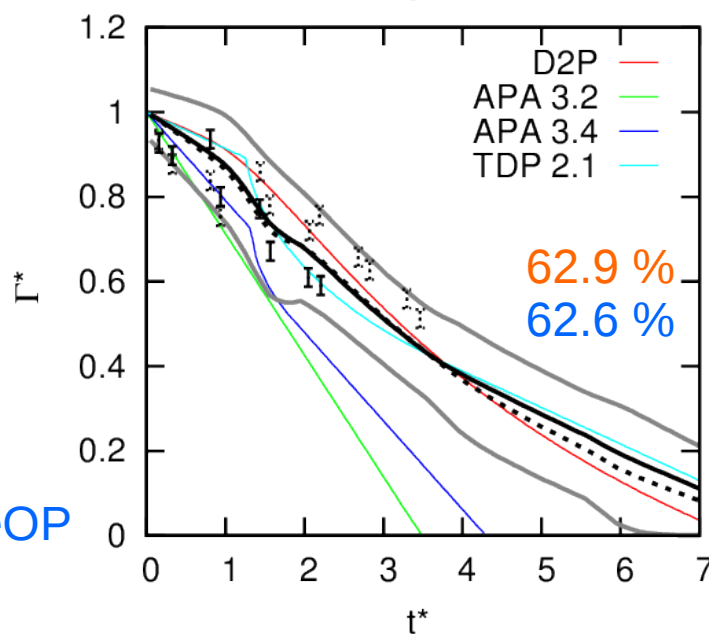
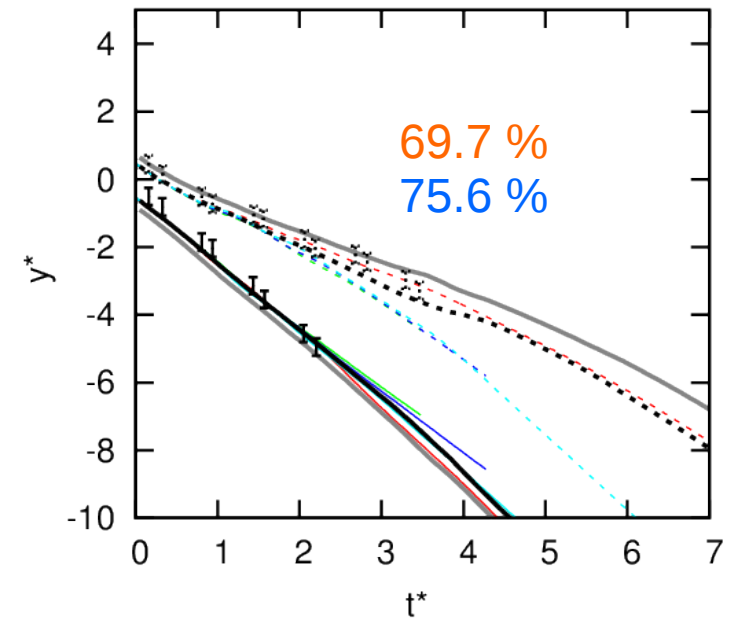
probability levels
according to

- 99 testcases
- WakeFRA & WakeOP

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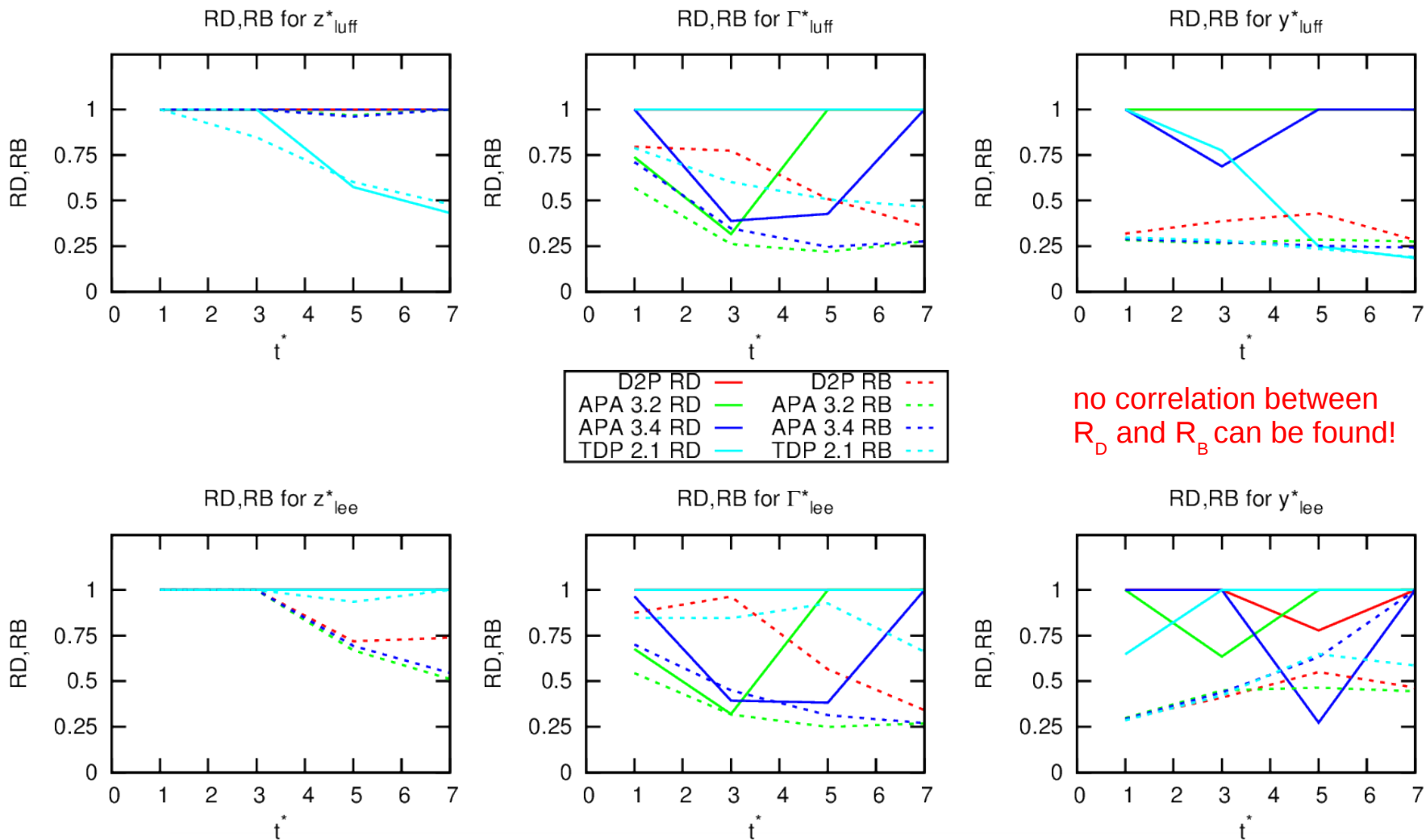


$b_0=51 \text{ m}$, $\Gamma_0=593 \text{ m}^2/\text{s}$



Results

REA reliability factors (one single landing)

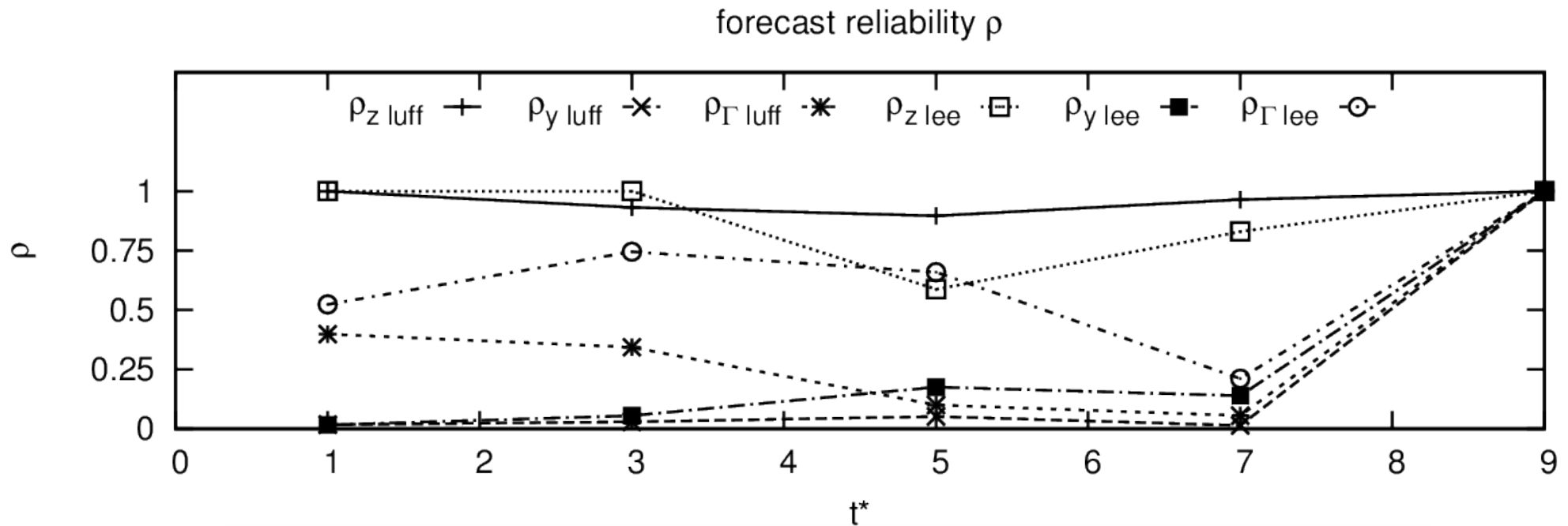


Results

REA forecast reliability (one single landing)

$$\tilde{\rho} = \frac{\sum_i R_i^2}{\sum_i R_i}$$

- low reliability for y - forecast
- high reliability for z - forecast
- medium reliability for Γ - forecast



Results

REA scoring

- 99 randomly chosen cases
- skill factor s :

$$s_i = \frac{\sum_{p=1}^n rmse_{e,p} / rmse_{i,p}}{n} - 1$$

2nd best

best

median	rms Γ_{luff}^*	rms Γ_{lee}^*	rms y_{luff}	rms y_{lee}^*	rms z_{luff}^*	rms z_{lee}^*	s
REA	0.116	0.099	0.433	0.409	0.163	0.149	0.000
TDP 2.1	● 0.127	0.106	0.590	0.415	0.237	0.147	-0.122
APA 3.4	0.160	0.107	0.602	0.413	0.179	0.154	-0.127
APA 3.2	0.204	0.140	0.612	0.410	0.179	0.154	-0.190
D2P	0.122	● 0.120	● 0.406	● 0.408	● 0.140	● 0.166	-0.016



Results

REA scoring

- 99 randomly chosen cases
- skill factor s :

$$s_i = \frac{\sum_{p=1}^n rmse_{e,p} / rmse_{i,p}}{n} - 1$$

2nd best

best

median	rms Γ_{luff}^*	rms Γ_{lee}^*	rms y_{luff}	rms y_{lee}^*	rms z_{luff}^*	rms z_{lee}^*	s
REA	0.116	0.099	0.433	0.409	0.163	0.149	0.000
DEA	0.131	0.093	0.525	0.411	0.173	0.149	-0.048



advanced MME approach outperforms
Direct Ensemble Average (DEA)

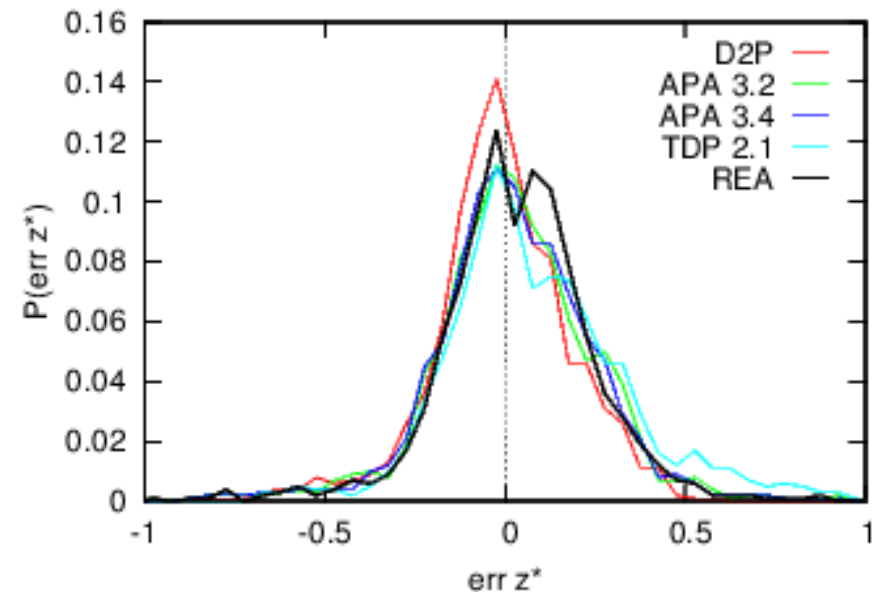


PDD of models and ensemble

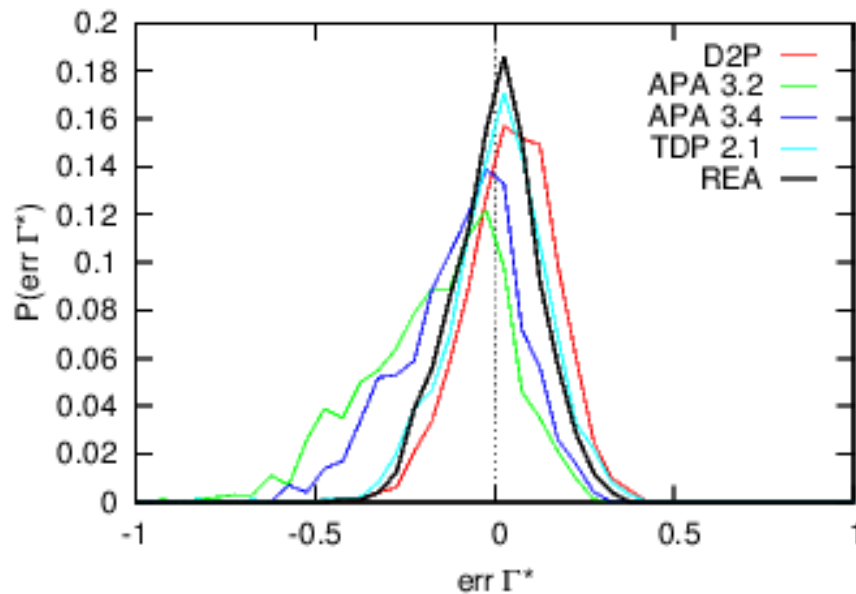
overconfident ensemble:
too narrow ensemble spread

well-dispersed ensemble:
coverage of full spectrum of
possible solutions

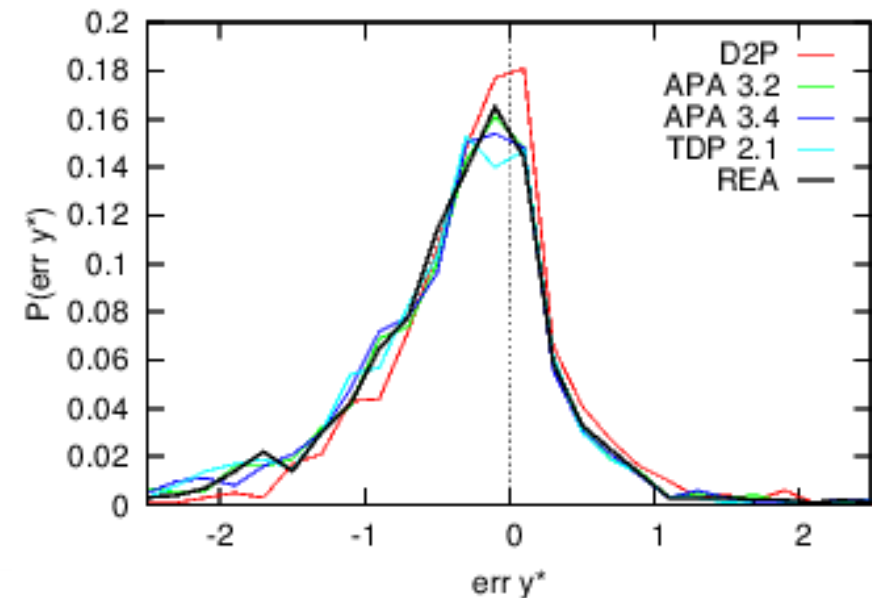
Weigel et al., 2008, Hagedorn et al., 2004



overconfident ensemble
→ small or no rmse improvement



well-dispersed model forecasts
→ rmse improvement



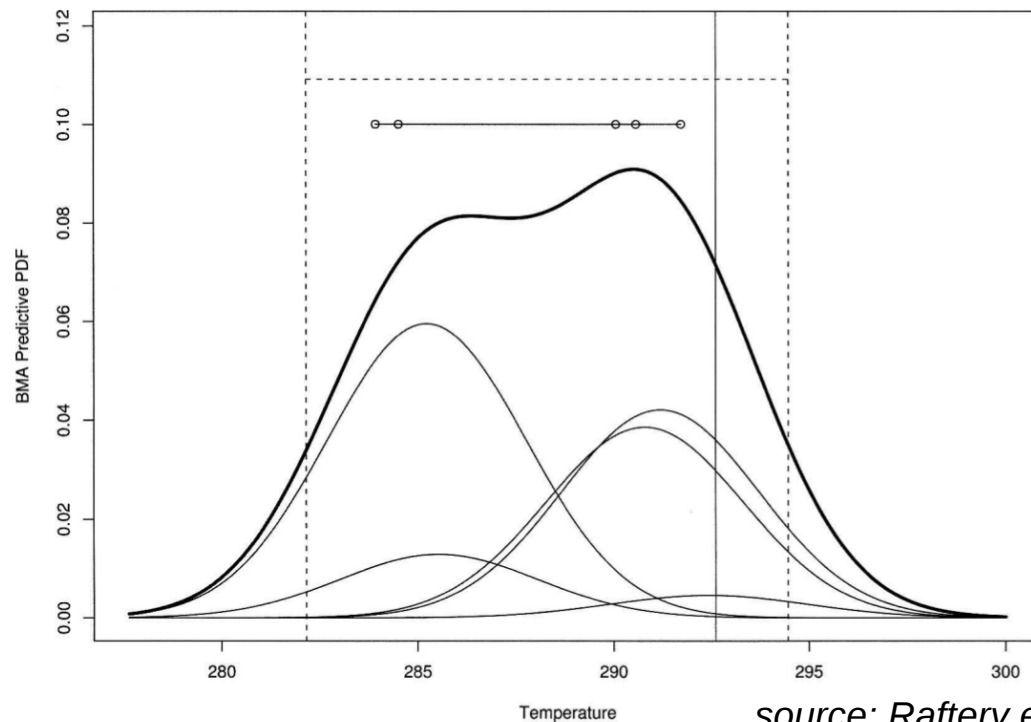
Conclusion

- ensemble **can improve quality** of wake vortex forecasts in average
- however **only 1.6 %** improvement compared to best model
- **reason:** ensemble is **overconfident** for z^* and y^*
- **but:** models might behave differently in particular ambient weather conditions and out-of-ground → investigation with pdds



Further Development

- How does **a good training data set** look like?
- Can the results be further improved by **distinguishing various ambient weather conditions**?
- How does the **Bayesian Model Averaging (BMA)** perform?



source: Raftery et al., 2005

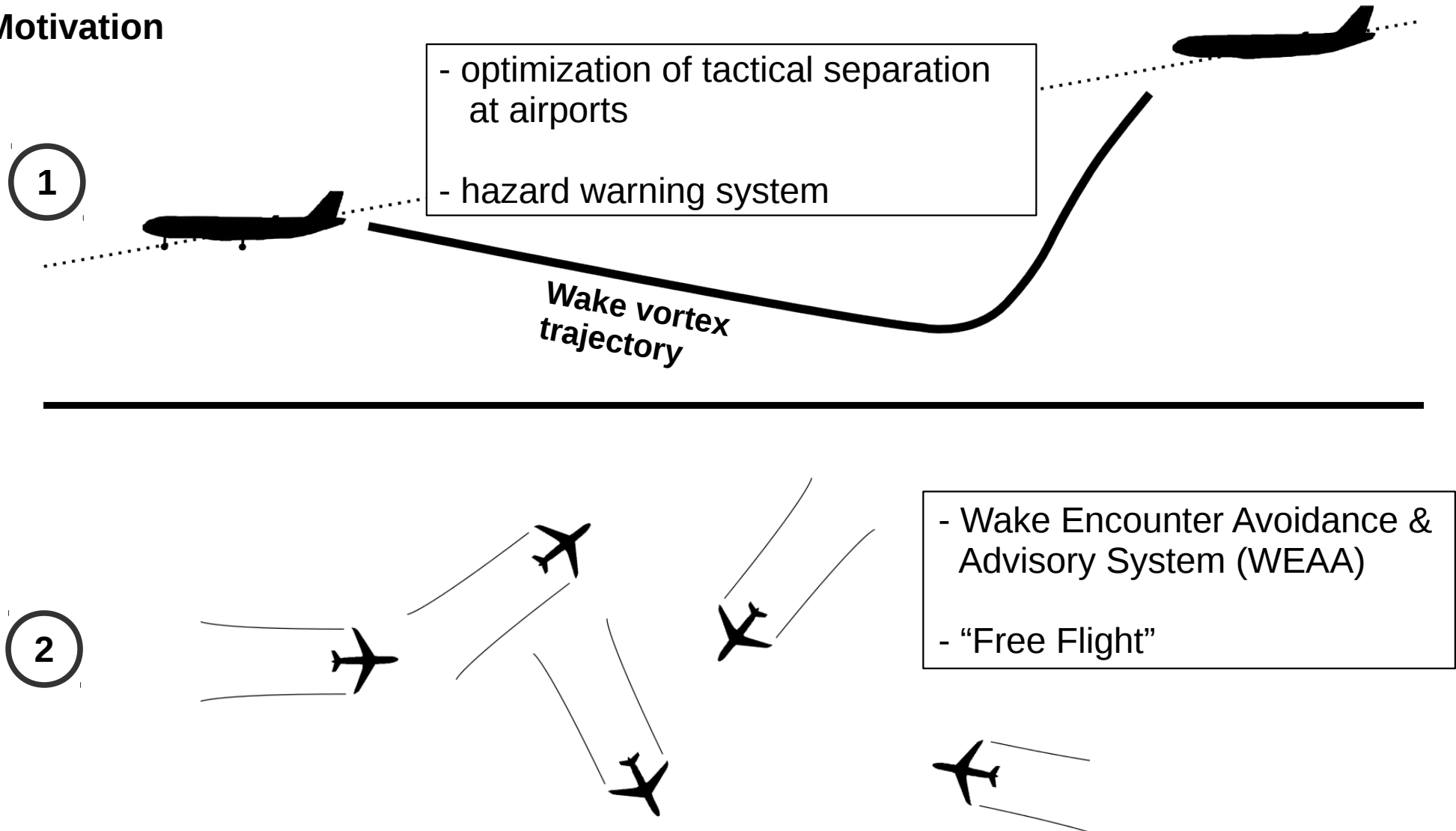


Backup



Wake Vortex Predictions

Motivation



Ensemble Methoden

Bayesian Model Averaging

$P(B)$ = Wahrscheinlichkeit des Eintretens von B

$P(B|A)$ = Wahrscheinlichkeit für B, unter Voraussetzung A

PDF = Probability Density Function (Wahrscheinlichkeitsdichtefunktion)

Law of total probability:

$$P(B) = \sum_n P(B \cap A_n) = \sum_n P(A_n)P(B|A_n)$$

Beispiel:

Wir befinden uns auf einem Schiff:

- wir wollen die Position B bestimmen
- 3 Crew-Mitglieder (A1,A2,A3) wissen wie es geht, haben aber unterschiedliche Methoden

according to Grimmer and Welsh., 1986


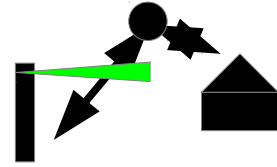


Ensemble Methoden

Bayesian Model Averaging

Law of total probability:

$$P(B) = \sum_n P(B \cap A_n) = \sum_n P(A_n)P(B|A_n)$$

Methode	A1	A2	A3
			$\vec{s} = \sum_n \vec{v}_n * t_n$
individuelle Wahrscheinlichkeit, dass die Methode Erfolg hat: $P(B A_n)$	0.6	0.9	0.7
Wahrscheinlichkeit, dass wir A1, A2 or A3 fragen: $P(A_n)$	0.2	0.5	0.3

➔ $P(B)=0.78$


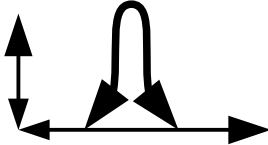
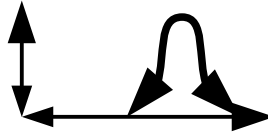


Ensemble Methoden

Bayesian Model Averaging

Law of total probability:

$$P(B) = \sum_n P(B \cap A_n) = \sum_n P(A_n)P(B|A_n)$$

Methode	A1	A2	A3
PDF der Methode (Modell-Unsicherheiten): $P(B A_n)$			
Wahrscheinlichkeit, dass wir A1, A2 or A3 fragen: $P(A_n)$	0.1	0.6	0.3



Ensemble Methoden

Bayesian Model Averaging

Law of total probability:

$$P(B) = \sum_n P(B \cap A_n) = \sum_n P(A_n)P(B|A_n)$$

angewandt auf Vorhersage-Modelle:

**Annahme: es gibt immer
ein bestes Ensemble-Glied**

A_n = Modell n

B = vorherzusagende Größe

B^T = Trainings-Daten

$P(A_n)$ = Wahrscheinlichkeit, dass A_n das beste Modell ist

(**Gewichtungsfaktor**, basierend auf B^T)

$P(B|A_n)$ = **PDF** of A_n alone (Gaussian distribution, given that A_n is the best forecast)

≙ gewichtete Summe von Wahrscheinlichkeitsdichtefunktionen (PDFs)

according to Raftery et al., 2005

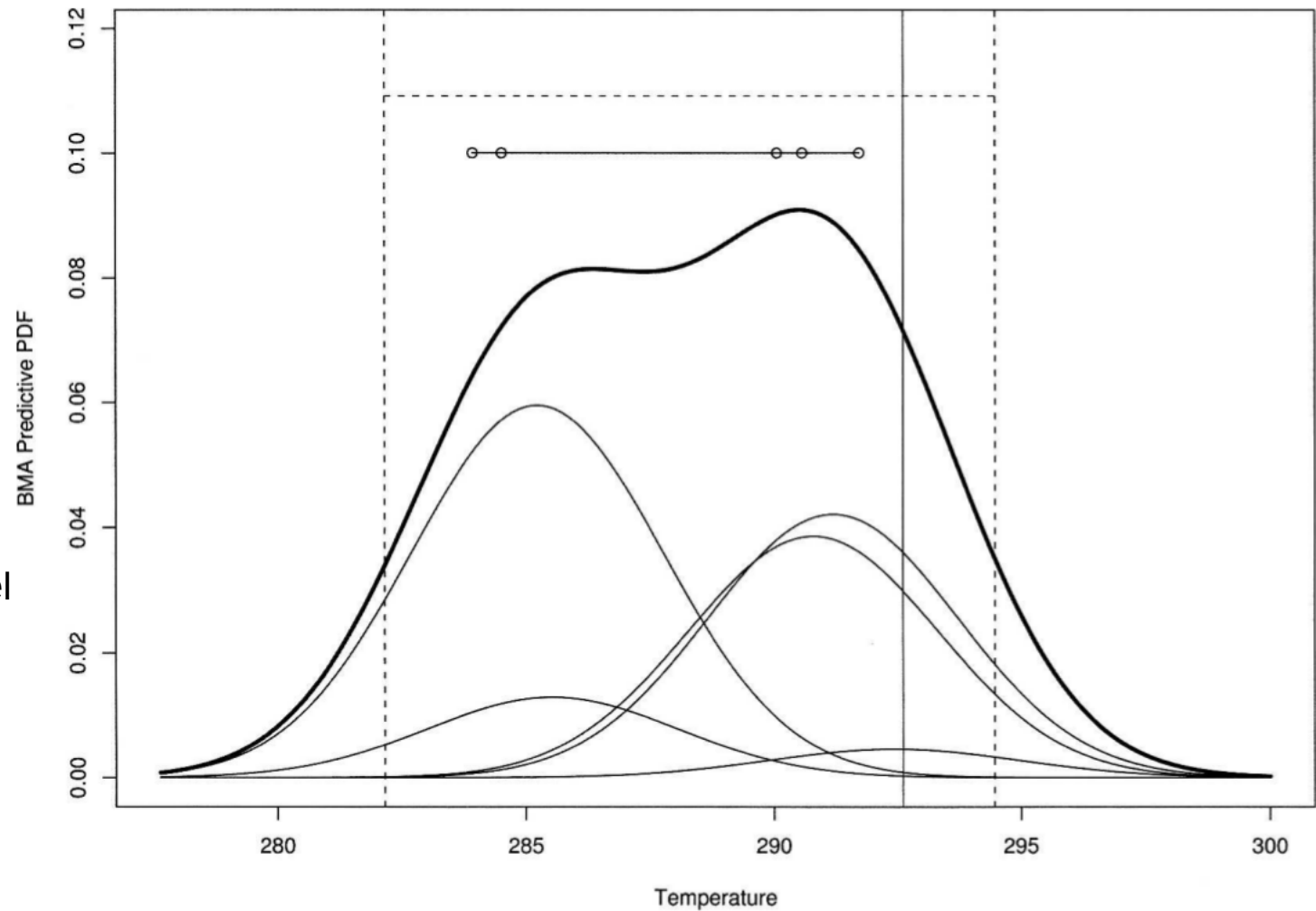


Ensemble Methoden

Bayesian Model Averaging

BMA applied on
48-h surface
temperature
forecast (bias
corrected)

- ↔ ensemble forecast
- ↔ individual model PDF
- individual model forecast
- ◆◆ 90% interval
- ◆ verification



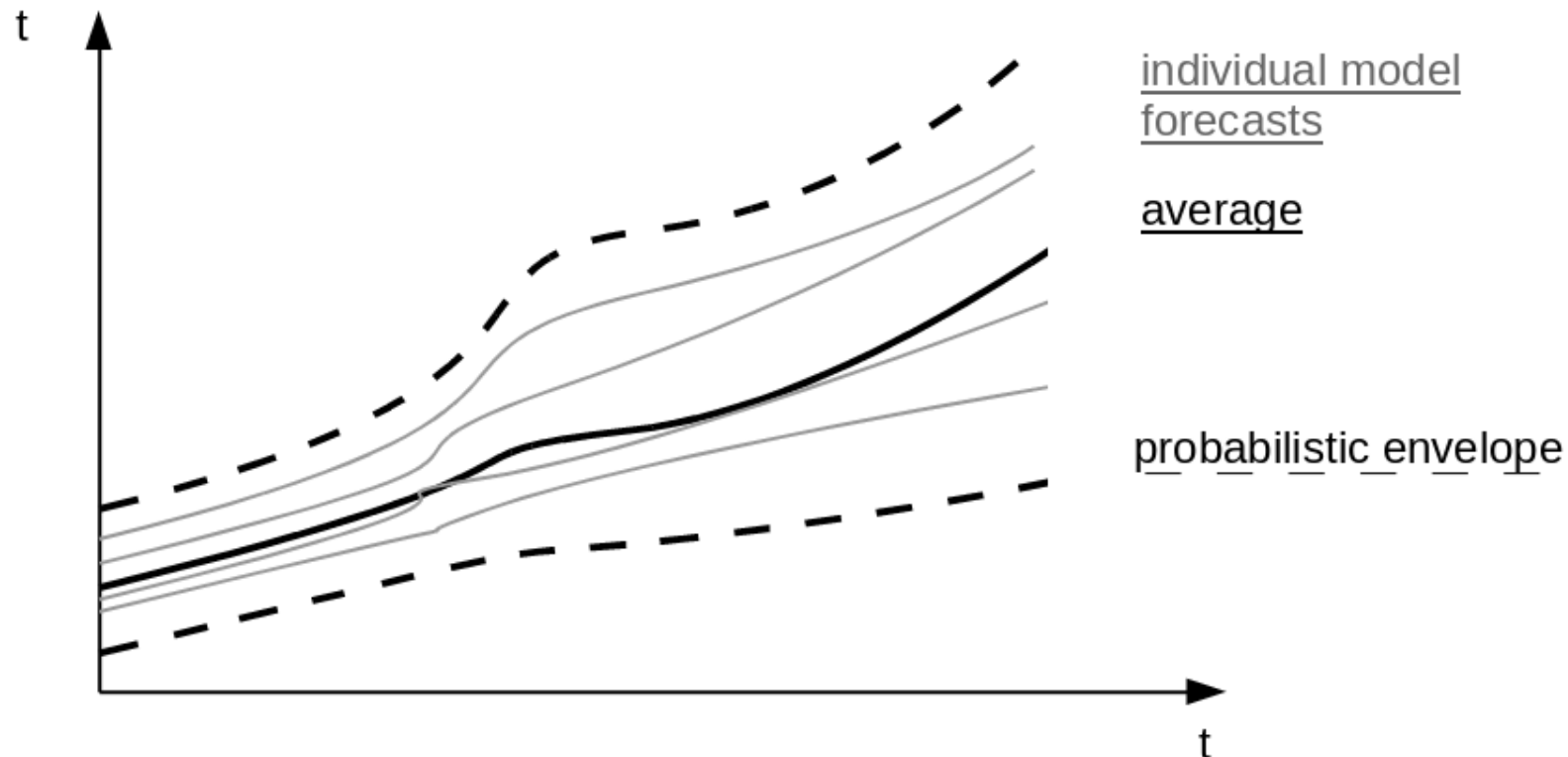
source: Raftery et al., 2005



Multi-Model Ensemble

benefit

- increase deterministic skill
- predict forecast skill
- provide probabilistic forecast



Multi-Model Ensemble

